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Manipulating basic characteristics of the Rapid Automatized Naming task in search for its most reliable connections to reading performance

Eugene Borokhovski
Concordia University, Montreal, Canada
E-mail: eborokhovski@education.concordia.ca

Abstract

Introduction. Connections between Rapid Automatized Naming (RAN) task performance and reading are well documented. Primary empirical studies and meta-analyses established and described associations between specific RAN subtasks and reading outcomes. The cognitive nature of these associations, however, remains largely underexplored. This study attempts to address the issue by explicitly manipulating some critical characteristics of the RAN task (stimuli types, combinations, and familiarity) and conditions of its administration (attention demand) in search for factors that affect RAN performance and underlie its connections to reading competencies.

Method. Ten modified RAN subtasks were created by manipulating type and familiarity of the stimuli, size of the stimuli source set, and demand to attention (cognitive controlled processing), involved in RAN performance. Measures of ballistic and efficiency-based automaticity, attention control, and reading rate were collected and analyzed using, ANOVA – with respect to performance on modified RAN subtasks, and correlational and multiple regression analyses – to address interrelations among major independent variables and their connections to reading rate.

Results. The study found differential sensitivity of the RAN performance to the explored experimental manipulations. Specifically, significant main effects on naming speed were observed for stimuli type, stimuli familiarity and attention demand. RAN performance on most of the modified subtasks (seven out of ten) was significantly correlated with the measure of attention control, whereas only one correlation between RAN and measures of automaticity was statistically significant. Findings of multiple regression analyses confirmed this pattern of results. Attention factor explained substantially larger portion of variance in performance on modified RAN than both indices of automaticity combined. Reading rate was significantly correlated with bigram-based RAN (supposedly reflecting practice), and its correlations with other modified subtasks were higher for the elevated attention demand conditions, in one case exceeding significance level.

Discussion. Understanding the cognitive nature of RAN is important for informing instructional practice of what reading skills might require special attention. This study

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explored specific conditions to which RAN performance may be especially sensitive. Modified RAN subtasks were markedly influenced by experimental manipulations, especially with regard to attention demand, indicating that attention, more than automaticity, could be a factor underlying naming speed as a predictor of reading.

Keywords

Rapid Automatized Naming (RAN), literacy, reading, automaticity, attention, symbolic RAN stimuli, non-symbolic RAN stimuli, modified RAN subtasks, naming speed, bigram frequency, cognitive mechanisms of RAN performance

Highlights

► RAN task performance is sensitive to the explicit manipulation of the attention factor, whereas the set size factor played much more modest role in affecting naming time.

► Neither 'ballistic' nor efficiency-based automaticity made substantial contribution to explaining variability in RAN task performance.

► General attention demand emerged as a strong predictor of performance practically on all (original and modified) RAN tasks.

► Stimulus familiarity, being a function of frequency of occurrence in printed text and exposure through practice in reading, appeared to be an important factor in linking RAN task performance to reading rate.

For citation

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Introduction

The role that naming speed phenomenon, as assessed by performance time on various forms of so-called Rapid Automatized Naming (RAN) task [1, 2] plays in anticipating reading outcomes has been repeatedly addressed in the research literature [e.g., 3, 4, 5], including several related meta-analyses [6, 7, 8]. Correlations between RAN and reading rate, specifically, though ranging in magnitude from study to study were quite consistent, regardless whether or not the researchers subscribed to the explanations offered by the double-deficit framework [9, 10, 11]. By now, the RAN task as a correlate/predictor of reading is not in question, though the strength of this association varies substantially – from nearly zero to considerably high, as reflected in the most comprehensive meta-analysis [6] – depending on both specific RAN tasks and reading outcomes. There remain, however, many

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important questions about the cognitive nature of performance on the RAN task that underlies its association with reading [e.g., 3, 4, 12]. Numerous hypotheses have been proposed since the test first appeared [13], but hardly any provides a full explanation of what might be behind the association between reading and RAN performance. The only real consensus rather stipulates the need for better understanding of possible cognitive nature of RAN-to-reading association. Consider, for example: "The arguments … are highly speculative and represent work in progress… Considerable further work is needed before these relationships will be sufficiently clarified" [14, p. 396]. This and similar statements in [3, 4] illustrate that empirical research is still far from an unequivocal solution to the question of why RAN task performance is associated with reading, even several decades after the test was launched.

The goal of the present work is to shed some light on the nature of the RAN task and its association with reading performance by experimentally addressing several important issues regarding conditions to which actual RAN task performance may be especially sensitive. Understanding the cognitive nature of RAN might lead to improving instruction in reading by targeting skills and competencies identified as potentially vulnerable by the corresponding deficiencies in RAN task performance.

Objectives and Rationale

The current study was designed to complement findings reported in [15] by experimentally addressing issues that had arisen there as well as to clarify those documented in [6]: (1) strong involvement of attention in RAN task performance and (2) substantial difference between symbolic and non-symbolic RAN subtasks performance and in their associations to reading outcomes. Subsequently, the study was guided by the following research questions:

How sensitive is RAN task performance to explicit manipulation of attention demands?

How important to RAN task performance is the "set size" factor, that is, the size of the source set from which the actual target stimuli are drawn from?

Does stimulus familiarity, as function of frequency in printed text, play any role in RAN task performance and its link to reading rate?

As shown in [15], attention-related factors influence RAN task performance and its connection to reading. Also, previous research has made a clear case for difference among various RAN subtasks in both these measures [e.g., 3, 4, 16]. Performance on the symbolic (letters and digits) and non-symbolic (colors and objects) RAN subtasks were not only significantly different in terms of time and supposedly some the underlying mechanisms, but more importantly, in the patterns of connection between RAN and reading outcomes [6].

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The following assumptions guided the design and implementation of the current study. RAN task performance, aside from its articulation component (voicing out the stimuli), rests on the two major types of expertise: (1) the ability to quickly recognize each individual stimulus in the presented sequence and establish a link to its correct name (transforming that name into the appropriate speech sounds) and (2) the ability to efficiently disengage from each already named individual stimulus and engage with the naming of the subsequent stimulus. The first assumption is fully consistent with the framework provided by the double-deficit hypothesis, whereas the second assumption emphasizes the potential role of attention-related factors. There is also a possibility that successful performance on RAN tasks relies on ability to process large sequences of individual stimuli, thus implicating attention in an even broader sense. Viewed from this perspective, automaticity of stimulus recognition and efficient management of attention resources remain the two potentially greatest contributors to naming speed.

Carefully weighing these two in the light of findings of [15], it seems plausibly that the RAN task is less dependent on automatic processing, at least at the level of single stimulus recognition and much more – on the ability to adequately direct and efficiently shift the respondent's attention. Initially (in children just learning how to read), all RAN subtasks are good predictors of reading outcomes. With time and practice in everyday reading, the growing familiarity with letters and digits may help to perfect performance of naming them, making this process more automatic. This automatized ability, however, cannot completely replace the important contribution of attention, and that is why, perhaps, the role of attention in naming non-symbolic stimuli does not diminish over time. Non-symbolic naming might even become more demanding because practice with language creates additional mental representations that have to be searched for proper names (written and spoken ones) of a very large number of objects (effectively unlimited), whereas the representations of letters and digits remains more or less the same.

Under these circumstances, the predictive power of symbolic RAN tasks for reading remains intact. Performance on the non-symbolic RAN tasks, on the contrary, is no longer connected to reading competency to the same extent. Other, more powerful factors (growing vocabulary, real life experience and academic knowledge, etc.) are coming into play. In other words, symbolic RAN task performance is based upon two major factors (first and foremost, it depends on the effects of practice, and somewhat secondarily on attention), whereas non-symbolic RAN task performance still mostly relies on the efficiency of attention control. One could say that, for regular readers, the "A" in RAN should really stand for attention, not automaticity (at least, not only), but to a different extent for the symbolic and non-symbolic subtasks.

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Experimental Framework

If the above account is correct, it is worth looking more closely at what stimuli features matter the most when used in symbolic and non-symbolic RAN subtasks. Presumably, some combination of the following factors needs to be considered:

Natural sequencing. It should be important to examine the contribution of stimulus sequencing in the performance of the RAN task. For example, letters and digits are more likely than objects or colors to be processed in short sequences (letters as bigrams or trigrams, digits as two or three digit sequences), whereas objects and colors are not likely to be chunked as sequences of two or three items. Practicing reading and dealing with numbers presents a person with a rich set of sequential experiences, so that some combinations should become familiar than others, because they are just more frequent and hence are more likely to be perceived and processed in sequence.

Symbolic/Non-symbolic status of the stimulus. The nature of the link between a stimulus and its name (which also determines some basic inherited difference between symbolic and non-symbolic stimuli in RAN) may be important. For example, a given letter of the alphabet will evoke its name because the visual form the item takes will normally closely resemble some basic (prototypical) mental representations of that item. In the case of objects, a given line drawing used as a stimulus in the RAN task may depart greatly from a mental representation of the prototype for that object (e.g., a picture of a clock will likely not correspond directly to the prototypical mental image of a clock as much as does, say, the letter "A" correspond to a mental image of an "A").

Size of the stimulus source set. It should be important to examine the impact of the total number of potential stimuli in the source "universe" (i.e., its full source set), which the stimuli used in a given RAN task subset was drawn from (e.g., the 26 letters of the alphabet or the 10 digits as compared to the virtually unlimited number of objects or substantially smaller but still very considerable number of shades of different colors).

Attention load handling demands. Finally, individual differences in how efficiently attention resources are managed should substantially influence RAN performance across all types of stimuli, if indeed attention remains an important determinant of the RAN task performance.

To test these assumptions, the RAN subtasks were modified to manipulate the factors of (1) familiarity in combinations of symbolic stimuli (relative frequency of bigrams), (2) source set size, and (3) attention load demands – with the two last factors varying within the two stimulus types (symbolic and non-symbolic), as follows.

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Modified Versions of the RAN Task

Overall, ten modified RAN subtasks were developed for this study. Two of them addressed the difference in familiarity with the elements of printed text by using as stimuli (symbolic) bigrams of different relative frequencies as they appear in printed English texts. The same 5 letters – *a, d, o, p,* and *s* – as used in the original letter naming RAN subtask were put into pairs in all possible combinations, and the relative frequency for each bigram was obtained using data from [17]. For example, the English bigram *sa* has a high relative frequency of 11.4 (number of appearances per 1000 characters in an average printed text), whereas the bigram *ao* is extremely rare, appearing in printed texts on average only 0.2 times per 1000 characters. These relative frequencies then were used to create two bigram-based versions of the letter naming RAN subtask. In the High Frequent version, the mean of the relative frequencies of all the bigrams used was 7.86, whereas in the Low Frequent version the mean was only 2.54. The "5 lines by 10 items per line" matrix used in the RAN task yielded a set of 9 x 5 = 45 bigrams (the pairs formed by the last letters of each line with the first letters of the next line not counted). As in the original letter naming RAN subtask, each of the 5 stimuli appeared 10 times in the High Frequent and Low Frequent modified versions.

The remaining 8 modified versions of the RAN task were constructed by manipulating the following characteristics: (1) symbolic versus non-symbolic nature of the stimuli, (2) heavy versus light attention load, and (3) source set size (large versus small). These manipulations were crossed (2 x 2 x 2) to yield the 8 new RAN subtasks.

Stimuli type. The symbolic RAN subtasks used letter stimuli and the non-symbolic subtasks used pictures of objects and animals.

Source set size. In the symbolic RAN subtask, the Large set size version used 5 consonants *(d, n, p, s,* and *v*) as stimuli and the Small set size version used 5 vowels (*a, e, i, o*, and *u*). In the non-symbolic RAN subtask, the Large set size version used line drawings of 5 unrelated objects (*bell, book, clock, flag,* and *star*) as stimuli and the Small set size version used line drawings of 5 pictures of animals (*bear, cat, cow, dog,* and *pig*). The names of the pictures were matched for length and all were drawn from nouns with relatively high frequencies.

Attention load. Attention was manipulated by asking participants to perform a concurrent activity while naming stimuli that appeared on the screen. In the Light Attention Load condition, the participants were required to press the space bar on the computer keyboard each time they named the last stimulus in the row (i.e., five times to simply indicate the completion of each line), without otherwise pausing in reading the names of the stimuli. In the Heavy Attention Load condition, the participants were required to press the space bar on the computer

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keyboard each time a particular combination of stimuli was encountered, without otherwise pausing in reading the names of the stimuli (participants were instructed as to what particular stimulus pair watch for). The target pair occurred 5 times to match the criterion for the space bar pressing in the other condition.

To summarize, there were 10 modified RAN subtasks:

1. M-RAN-High-Frequency-Bigram (here and further M stands for "modified") subtask used high frequency bigrams (consonants and vowels).
2. M-RAN-Low-Frequency-Bigram subtask used low frequency bigrams.
3. M-RAN-Symbolic-Small-Light subtask used letter stimuli (*symbolic*) – vowels (*small* source set) with the *light* attention load directive (press 'space bar' at the end of each line).
4. M-RAN-Symbolic-Small-Heavy subtask used letter stimuli (*symbolic)* – vowels (*small* source set) with the *heavy* attention load directive (press 'space bar' upon encountering a designated stimulus pair).
5. M-RAN-Symbolic-Large-Light subtask used letter stimuli (*symbolic*) – consonants (*large* source set) with the *light* attention load.
6. M-RAN-Symbolic-Large-Heavy subtask used letter stimuli (*symbolic*) composed of consonants (*large* source set) with the *heavy* attention load.
7. M-RAN-Non-symbolic-Small-Light subtask used picture (*non-symbolic*) of animals (*small* source set) with the *light* attention load.
8. M-RAN- Non-symbolic-Small-Heavy subtask used pictures (*non-symbolic*) of animals (*small* source set) with the *heavy* attention load.
9. M-RAN- Non-symbolic-Large-Light subtask used pictures (*non-symbolic*) of unrelated objects (*large* source set) with the *light* attention load.
10. M-RAN- Non-symbolic-Large-Heavy subtask used pictures (*non-symbolic*) of unrelated objects (*large* source set) with the *heavy* attention load.

The following outcomes were hypothesized. Regarding the comparison between bigram-based versions of the RAN task, it was expected that the processing of higher frequency bigrams would proceed faster, resulting in shorter RAN performance time (hypothetical Scenario 1 in Figure 1).

With respect to the eight RAN subtasks involving orthogonal manipulations of symbolic versus non-symbolic stimuli, light versus heavy attention load and larger versus small source set, we hypothesized the following.

Slower performance on non-symbolic subtasks, as less familiar and hence less automatized in processing – due to higher variability in how the recognized stimulus is mapped to its proper label (Figure 2);

Heavy attention load will slow down RAN performance if attention control is instrumental in the rapid naming (Figure 3);

Stimuli drawn from the larger source set will be named slower than stimuli drawn from the smaller source set (Figure 4).

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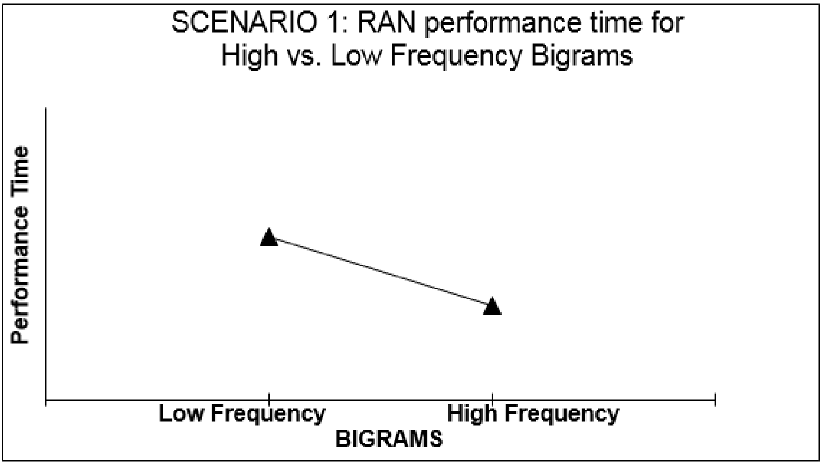

Figure 1. A hypothetical scenario reflecting expected pattern in performance times on bigram-based modified RAN subtasks

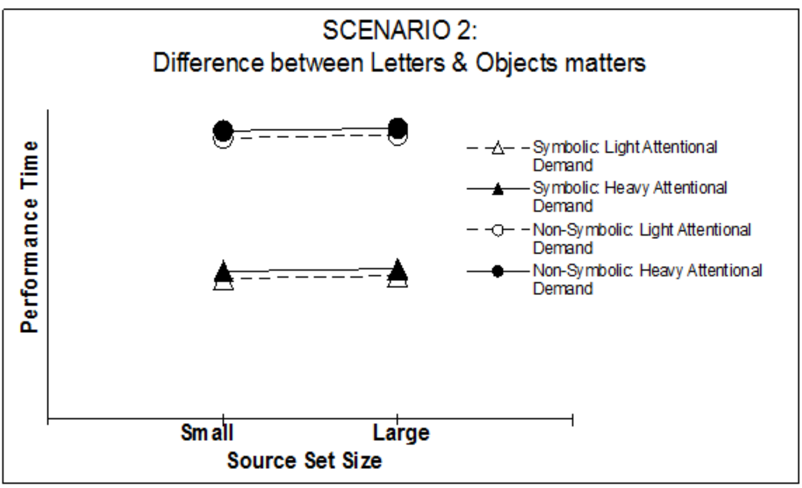

Figure 2. A hypothetical scenario reflecting expected pattern in performance times on modified RAN subtasks if stimulus type matters the most

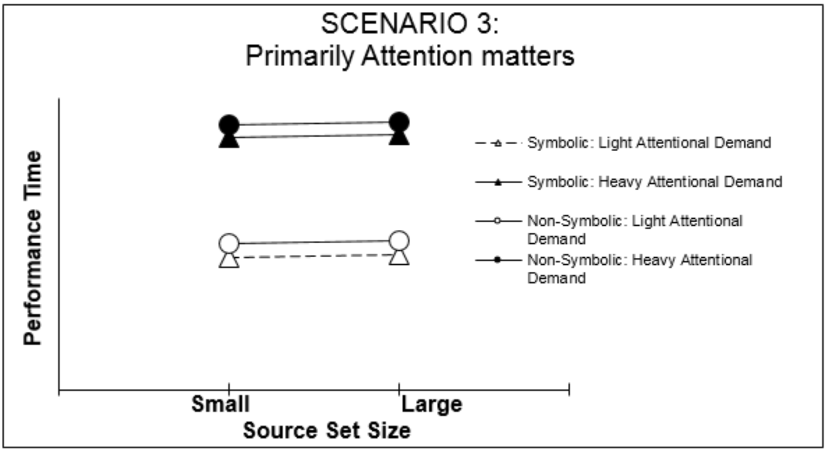

Figure 3. A hypothetical scenario reflecting expected pattern in performance times on modified RAN subtasks if attention matters the most

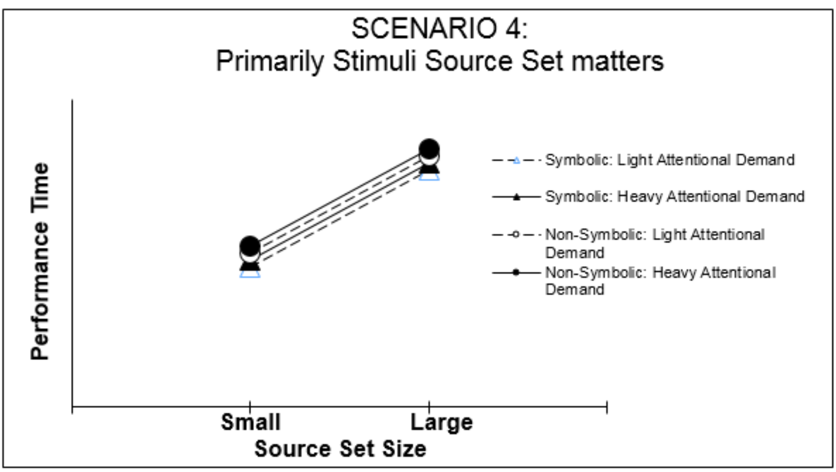

Figure 4. A hypothetical scenario reflecting expected pattern in performance times on modified RAN subtasks if source set size matters the most

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If observed: (1) Scenario 1 would affirm the frequency/familiarity account for explaining RAN task performance and its likely link to reading; (2) Scenario 2 would affirm the automaticity account; (3) Scenario 3 would affirm the attention account; and (4) Scenario 4 would affirm the source set account. Of course, only main effects are projected here. With so many variables, a strong possibility of various interaction effects exists. There is no particular conceptual ground for confidently generating and sorting out these potential interaction effects, however, one stands out as intuitively the most plausible (Figure 5).

This last scenario depicts the possibility that attention demand and source set size would affect RAN performance differently in symbolic and non-symbolic subtasks. Namely, in more automatized symbolic subtasks source size would influence performance time to a greater extent, while non-symbolic subtasks that are more attention-based would be more sensitive to manipulations of the attention load factor.

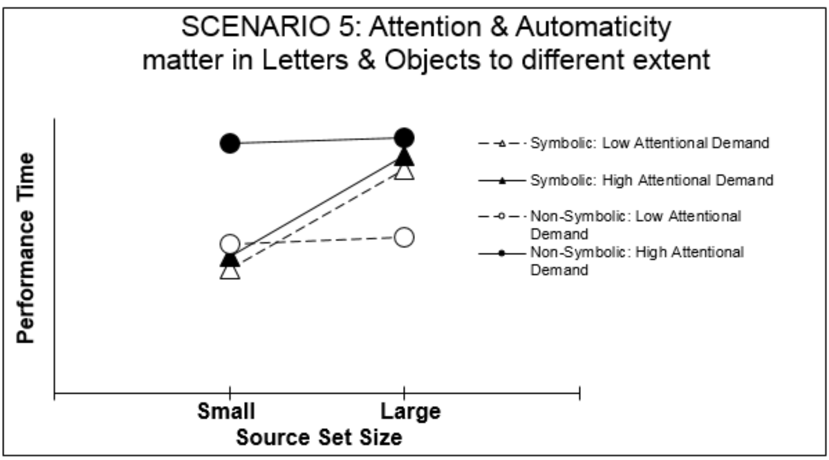

Figure 5. A hypothetical scenario reflecting expected pattern in performance times on modified RAN subtasks if attention and source set size influence naming speed symbolic and non-symbolic subtasks to a different degree

As revealing about the cognitive underpinnings of the RAN performance as these modified versions of the task could be, they are in the focus of this study not just per se, but in connection with the reading outcomes. Besides the likely (inherently strong) association between performance on symbolic RAN subtask and reading rate, we hypothesized that the more challenging modified RAN subtasks (the ones resulting in overall slower naming speed) would also show

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a higher degree of association with reading rate, thus confirming the greater role of the corresponding factors in it with respect to reading. This expectation is based on the assumption that a shared set of cognitive mechanisms underlies both RAN and reading performance, thus making the former a reliable predictor of the latter.

Method

Participants. Sixteen participants (11 women and 5 men, ranging in age from 19 to 42 with the mean of 24.5, median of 22.5, and the mode of 21), predominantly Psychology undergraduate and graduate students, composed the sample for the study, randomly selected from the pool of participants of [15]. As such they all undertaken the entire set of test activities there, just supplemented by administration of the modified RAN tasks in the current study. Thirteen named English as their dominant language, and the remaining three were fluently bilingual (French-English). All participants signed a standard (approved by the University ethical committee) consent form were compensated (20$ CA) for their participation in the experiment and upon its completion were debriefed – i.e., informed of the purposes of the study and given an opportunity to ask related questions.

Materials. Ten modified versions of the RAN task manipulating three factors – attention load, source set size, stimulus type and familiarity factors – comprised the main test activity:

M-RAN-High-Frequency-Bigram. Five letters – *a, d, o, p,* and *s*, – each repeated ten times were mixed to produce pairs (bigrams) with the highest possible index of relative frequency, as determined in [17].

M-RAN-Low-Frequency-Bigram. Five letters – *a, d, o, p,* and *s*, – each repeated ten times were mixed to produce pairs (bigrams) with the lowest possible index of relative frequency, as determined in [17].

For the remaining modified subtasks the stimuli were orthogonally varied as follows:

The subtasks *M-RAN-Symbolic-Small-Light* and *M-RAN-Symbolic-Small-Heavy* used as stimuli the vowels: *a, e, i, o,* and *u* (symbolic; small source set) and presented with the Light Attention load (the task of pressing a space bar each time when the last character in each raw is named) and the Heavy Attention load instructions respectively (the task of pressing a space bar in response to each encounter of the combination "*e-a*").

The subtasks *M-RAN-Symbolic-Large-Light* and *M-RAN-Symbolic-Large-Heavy* used as stimuli the consonants: *d, n, p, s,* and *v* (symbolic; large source set) and presented either with the Light or Heavy Attention load, as described earlier (the target pair of consonant stimuli in the latter was "*n-p*").

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The subtasks *M-RAN-Non-symbolic-Small-Light* and *M-RAN-Non-symbolic-Small-Heavy* used of the animals: *bear, cat, cow, dog,* and *pig* (small source set) and presented either with the Light or Heavy ("*cow-dog*" as the target) Attention load.

The subtasks *M-RAN-Non-symbolic-Large-Light* and *M-RAN-Non-symbolic-Large-Heavy* used pictures of the unrelated objects: *bell*, *book*, *clock*, *flag*, and *star* (large source set) and presented either with the Light or Heavy ("*clock-star*" as the target) Attention load.

In addition, (and as part of the experimental procedure of [15], the following measures were administered in the current study.

The original four *RAN tasks*: symbolic – letters and digits and non-symbolic – objects and colors, presented in five rows, each containing ten stimuli – randomly mixed ten repetitions of five stimuli of each type.

Measures of ballistic and efficiency-based automaticity included two indices of a person's ability to perceive and process target stimuli automatically. The first addressed the degree to which participants were capable of recognizing simple stimuli – letters and digits – in a ballistic (unstoppable) manner. The procedure used was based on so-called "primed decision" experimental paradigm [18, 19]. In this procedure, participants were given the task of judging whether a letter target was a vowel or a consonant, and whether a digit target was even or odd. Each target stimulus was preceded by another stimulus intended to prepared – or *prime* – participants for the upcoming target letter or digit. The design of the task made it possible to determine if the prime had been processed in a ballistic manner or not by extracting indices of the 'interference' effect (in the 'unexpected' – digits preceded by letters and vice versa – trials) and 'facilitation' effect (in the 'expected' – same category of primed and target stimuli – trials), both calculated in comparison with the 'neutral' trials, in which the target stimulus was preceded by a string of asterisks [20 – for details].

The second measure of automaticity – coefficient of variation (CV) or the ratio of standard deviation of reaction time to the mean reaction time – addressed the degree to which participants were able to process stimuli efficiently [21, 22]. This index is based on the idea of distinguishing between rapid task performance that is due simply to a speeding-up of all the underlying processing components and rapid task performance that is due to a restructured and more efficient deployment of underlying processing components. For the purposes of the current study the CV index was extracted for participants' performance on short stimulus onset asynchrony (SOA) 'neutral' primed trials – for details, please, see [20].

Attention control was measured by the "Trail Making" test [e.g., 23, 24]. In general, attention can be understood in terms of sustaining, focusing, dividing, suppressing, or shifting the concentration of conscious resources. Our focus of interest was on the efficiency of the attention shifting process as most reflective

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of participants' ability to manage the complex processing of large sequences of stimuli – the requirement, supposedly shared by the RAN task and reading. The test consists of two conditions that require participants to connect a set of 25 circles randomly distributed across a page. In one condition, the circles are numbered from 1 to 25 and must be connected in numerical order. In the other condition half the circles are labeled with numbers (1–12) and half with letters (A–M). The participant must connect the circles by shifting from letters to digits and back in the standard order (A-1-B-2...etc.). The difference in time between the shifting and non-shifting conditions provides an index of attention control (shift cost).

Finally, *Reading Performance* was assessed by measures of silent reading rate and comprehension using Nelson-Denny standardized test of reading skills [25], specifically, forms G and H – for college students. Each participant received two text fragments, about one page or 600 words long each, one at the beginning of the experimental session and one at the end, counterbalanced across participants. Participants were instructed to read silently as fast as possible while at the same time reaching full understanding of the text and being prepared to answer comprehension questions when finished. After the first minute of reading they were asked to mark the line they were reading at that. The number of words the participant had read in one minute served as the test measure of reading rate. In this study, however, following a suggestion in [26], reading rate was converted from words per minute to milliseconds per word and in this form entered all subsequent analyses as a measure of reading speed.

Design and Procedure. All participants completed the full set of tasks, outlined in the above section. All RAN subtasks (including the modified ones) were administered in the same mode as the original RAN subtasks were – on a computer screen of a G4 iMac in 5 rows of 10 items, using PsyScope software [27] with the performance time on each subtask recorded by the program.

In all other respects the current study matched precisely the procedure of [15], including administration of measures of silent reading rate and comprehension as well as of deriving the indices of different types of automaticity and attention shift cost. Presentation of the modified RAN subtasks was carefully counterbalanced across participants by conditions and proximity to other tasks, so that nobody received them in the same order in identical combinations with the neighboring activities and assessment tools.

Results

Modified RAN Subtasks

The naming times obtained for the 10 modified RAN subtasks were submitted to analyses as follows. First, to address the question of whether the bigram frequency had an impact on naming times, we compared the naming times

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for the M-RAN-High-Frequency-Bigram and the M-RAN-Low-Frequency-Bigram conditions. The results indicated that letter targets in sequences composed of highly frequent bigrams were named significantly faster than those in sequences composed of low frequency bigrams: $t = 3.276$, $p = .005$).

The next analysis addressed the questions about whether the symbolic versus non-symbolic nature of the RAN task stimuli, the source set size, and attention load all play roles in RAN task performance and whether there are interactions between these factors. For this purpose, the naming times were submitted to a 2x2x2 repeated measures ANOVA where the factors were Type (symbolic, non-symbolic stimuli), Source Set Size (large, small) and Attention Load (heavy, light). As expected, the analysis revealed a significant main effect for stimulus type (F (1,15) = 131.22, MSe =70,787,953.39, $p < .001$, partial $\eta^2 = .897$), indicating faster naming for symbolic stimuli. The analysis also revealed a significant main effect for attention load (F (1,15) = 62.12, MSe = 27,543,164.06, $p < .001$, partial $\eta^2 = .806$), indicating faster naming under the light attention demand. There was no main effect for source set size (F (1,15) = 1.063, $p > .05$). See Figure 6, and Table 1 for the ANOVA summary.

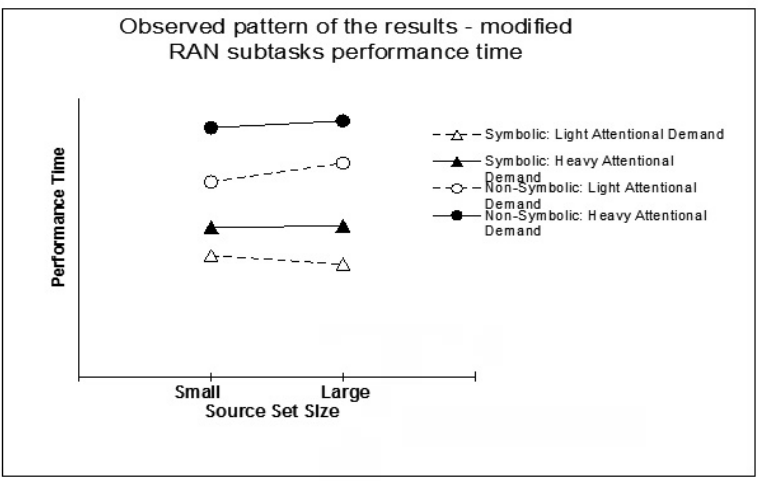

Figure 6. Observed pattern of performance times on modified RAN subtasks

The 2x2x2 interaction effect was not significant, suggesting that the effects of attention and stimulus type were consistent across conditions. However, there was a significant interaction effect of stimulus source set size by stimulus type (F (1,15) = 18.973, MSe = 3,775,251.33, $p = .001$, partial $\eta^2 = .558$). The nature of this interaction was that among non-symbolic stimuli, those drawn from

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a smaller source set (pictures of animals) were named significantly faster than those drawn from a larger source set (pictures of unrelated common objects), whereas within the symbolic stimuli, the reverse was true: stimuli drawn from a smaller source set (vowels) were named significantly slower than those drawn from a larger source set (consonants).

Table 1. Performance on modified RAN subtasks – ANOVA summary

Source	*Df*	*F*	*MS*	*h*	*P*
Attention:					
Effect Error term	1 15	62.124	1711095750 27543164.1	.806	< .001
Stimulus type:					
Effect Error term	1 15	131.216	9288504253 70787953.4	.897	< .001
Source set size:					
Effect Error term	1 15	1.063	22266132.8 20950585.3	.066	.319
Attention x Type:					
Effect Error term	1 15	3.923	57467240.3 4648836.6	.207	.066
Attention x Size:					
Effect Error term	1 15	.079	164164.5 2078085.1	.005	.782
Type x Size:					
Effect Error term	1 15	18.973	71628480.5 3775251.3	.558	.001
Attention x Type x Size:					
Effect Error term	1 15	3.558	52790826.5 9214886.4	.192	.079

Relationships among Variables

Correlational analyses were run to examine the relationships among variables used as predictors of RAN task performance in the subsequent multiple regression analyses and their connections to reading. The results of these analyses are shown in Tables 2, 3.

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The pattern of inter-correlations among the individual RAN subtasks, both the original and the modified ones, emerged to be quite strong (not surprisingly because they overlap greatly in the basic task demand – rapid naming). RAN subtasks using stimuli of the same type composed pairs that were most highly correlated, whereas the least correlated RAN subtasks were those with stimuli of different types. For example, performance on the original letter-naming subtask was correlated with performance on the task requiring the naming of vowels (under both low and the high attention demand conditions), and with naming of frequent and rare bigrams (all $r \geq .690$, all p-values $\leq .01$). The same was true for the naming of common objects in the original and modified RAN subtasks (all $r \geq .64$, all p-values $\leq .01$).

Analyses of correlations between performance on the modified RAN subtasks and the reading measures and indices of automaticity and attention revealed the following patterns. Regarding correlations between indices of automaticity and performance on the modified RAN subtasks, only the CV index of automaticity was significantly correlated with the speed of naming vowels, under the light attention load condition ($r = .457$, $p = .038$). No other correlation with an automaticity index was statistically significant.

In contrast, correlations between indices of attention and RAN performance did yield several significant results. Performance time on Form B of the Trail Making test and the speed of naming consonants under the low attention load condition were significantly correlated ($r = .670$, $p < .01$). Also, it was correlated significantly with naming vowels, consonants, pictures of animals, and pictures of common objects ($r = .641$, $p < .01$; $r = .706$, $p < .001$; $r = .650$, $p < .01$; and $r = .618$, p < .01, respectively) under high attention load condition.

The correlations between performance on the modified RAN subtasks and reading rate were not strong. Only one of them (that is for RAN-M-Symbolic-Small-Heavy) reached significance ($r = .449$, $p = .040$). The correlation between RAN-M-Non-Symbolic-Small-Heavy and reading showed a trend only ($r = .365$, $p = .082$). However, the magnitudes of these correlations are compatible with the significant correlations between measures of RAN task performance and reading rate observed in [15], with the only difference that the small sample size was responsible for the lower power. Performance on both High-Frequency and Low-Frequency bigram-based RAN subtasks was strongly correlated with L1 silent reading speed ($r = .533$, $p = .017$, and $r = .638$, $p = .004$, respectively). Finally, when the correlations among variables in the current study were compared with the analogous correlations obtained in [15], the patterns of these correlations seemed fairly consistent.

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Table 2. Inter-correlation coefficients among original and modified RAN subtasks

VARIABLES:	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1. Letter-RAN	-													
2. Digit-RAN	.596**	-												
3. Color-RAN	.072	.331	-											
4. Object-RAN	-.066	-.086	.406	-										
5. M-RAN-Symbolic-Small-Light	.716**	.647**	.094	.128	-									
6. M-RAN-Symbolic-Large-Light	.475*	.675**	.583**	.350	.519*	-								
7. M-RAN-Non-Symbolic-Small-Light	-.016	.171	.474*	.805***	.264	.594*	-							
8. M-RAN-Non-Symbolic-Large-Light	-.055	.040	.325	.916***	.206	.430	.894***	-						
9. M-RAN-Symbolic-Small-Heavy	.737**	.612**	.562**	.176	.645**	.652**	.203	.325	-					
10. M-RAN-Symbolic-Large-Heavy	.462*	.341	.397	.723**	.542*	.647**	.762***	.672**	.633**	-				
11. M-RAN-Non-Symbolic-Small-Heavy	.306	.319	.517**	.586**	.327	.633**	.671**	.731**	.665**	.678**	-			
12. M-RAN-Non-Symbolic-Large-Heavy	.268	.338	.597**	.644**	.274	.737**	.755***	.764***	.580*	.750**	.907***	-		
13. M-RAN-High-Frequency-Bigram	.690**	.655**	.199	-.056	.569**	.624**	-.031	.137	.595**	.287	.214	.266	-	
14. M-RAN-Low-Frequency-Bigram	.722**	.740**	.471*	.029	.493**	.785***	.125	.276	.790***	.458*	.607**	.647**	.791***	-

** p < .05, ** p < .01, *** p < .001.*

The list of variables:

1 – RAN performance time on letters task; 2 – RAN performance time on digits task; 3 – RAN performance time on colors task;
4 – RAN performance time on objects task; 5 – Modified RAN: light attention load, vowel letters; 6 – Modified RAN: light attention load, consonant letters; 7 – Modified RAN: light attention load, pictures of animals; 8 – Modified RAN: light attention load, pictures of common objects; 9 – Modified RAN: heavy attention load, vowel letters; 10 – Modified RAN: heavy attention load, consonant letters; 11 – Modified RAN: heavy attention load, pictures of animals; 12 – Modified RAN: heavy attention load, pictures of common objects; 13 – Modified RAN: based on frequent bigrams; 14 – Modified RAN: based on rare bigrams.

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Table 3. Inter-correlation coefficients for the major variables

VARIABLES:	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1. M-RAN-Symbolic-Small-Light	-															
2. M-RAN-Symbolic-Large-Light	.519*	-														
3. M-RAN-Non-Symbolic-Small-Light	.264	.594*	-													
4. M-RAN-Non-Symbolic-Large-Light	.206	.430	.894***	-												
5. M-RAN-Symbolic-Small-Heavy	.645**	.652**	.203	.325	-											
6. M-RAN-Symbolic-Large-Heavy	.542*	.647**	.762***	.672**	.633**	-										
7. M-RAN-Non-Symbolic-Small-Heavy	.327	.633**	.671**	.731**	.665**	.678**	-									
8. M-RAN-Non-Symbolic-Large-Heavy	.274	.737**	.755***	.764***	.580*	.750**	.907***	-								
9. M-RAN-High-Frequency-Bigram	.569**	.624**	-.031	.137	.595**	.287	.214	.266	-							

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VARIABLES:	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
10. M-RAN-Low-Frequency-Bigram	.493**	.785***	.125	.276	.790***	.458*	.607**	.647**	.791***	-						
11. Ballistic automaticity	.262	-.081	-.058	-.077	-.193	-.091	-.273	-.384	.235	-.136	-					
12. Automati-city/ Efficiency	.457*	.211	.230	.306	.052	.164	.176	.199	.130	.142	.389	-				
13. Attention: Form B	.409	.670**	.320	.203	.641**	.706***	.650**	.618**	.515*	.573*	-.010	.062	-			
14. Attention shift cost	.254	.294	.404	.483*	.197	.537*	.318	.291	.165	.047	.107	-.068	.736***	-		
15. Reading rate (L1)	.170	.309	.176	-.024	.449*	.204	.365	.280	.533**	.638**	.132	-.091	.380	.011	-	
16. Reading rate (L2)	-.155	-.215	.224	-.001	.044	-.145	.195	.165	.316	.403	.053	.049	.208	-.116	.625**	-

* p < .05, ** p < .01, *** p < .001.

The list of variables*:*

1 – Modified RAN: light attention load, vowel letters; 2 – Modified RAN: light attention load, consonant letters; 3 – Modified RAN: light attention load, pictures of animals; 4 – Modified RAN: light attention load, pictures of common objects; 5 – Modified RAN: heavy attention load, vowel letters; 6 – Modified RAN: heavy attention load, consonant letters; 7 – Modified RAN: heavy attention load, pictures of animals; 8 – Modified RAN: heavy attention load, pictures of common objects; 9 – Modified RAN: based on frequent bigrams; 10 – Modified RAN: based on rare bigrams;11 – Facilitation effect ('Expect Unrelated' short SOA, surprise trials) – relative value (adjusted by the corresponding base-line condition); 12 – CV index ('Expect Related' short SOA, neutral trials); 13 – Attention: Form B performance time ("Trail Making" test of attention); 14 – Standardized residual (Form B against Form A performance time on the "Trail Making" test) as an index of the attention shift cost; 15 – Reading rate (ms/word) in first language; 16 – Reading rate (ms/word) in second language.

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Multiple Regression Analyses

To address the major research question about factors underlying RAN task performance, the data were submitted to a series of multiple regression analyses. First, here is a word of caution. The multiple regression statistical technique typically requires samples of much larger size [28] to produce more reliable results. Therefore, the findings discussed below should be treated very carefully to avoid premature conclusions. Even statistically very sound results, at best, represent just tendencies to be verified in follow-up studies on more diverse samples. For this reason, as well, adjusted (for a small sample size) R^2 are reported in addition to the statistics presented in the corresponding tables.

In these multiple regression analyses, performance on the modified RAN subtasks served as the criterion variables to be explained by the following predictor variables to determine what factors best explain the naming speed phenomenon:

(1) The index of ballistic automaticity (relative facilitation effect on surprise trials with the short SOA in the 'expect unrelated target' condition of the primed decision making task);

(2) The index of efficiency (automaticity) in stimulus recognition (the CV-index), calculated for neutral trials with the short SOA in the 'expect related target' condition of the primed decision making task; and

(3) The index of general attention (performance time on Form B of the Trail Making test).

The following statistically significant findings were obtained (please, see Tables 5 through 14 for details). The overall model for the consonant naming RAN subtask, i.e., involving symbolic stimuli from a large source set under the condition of light attention load, was significant ($R^2 = .501$, adjusted $R^2 = .376$, $p = .034$). It was the only significant result for the condition of light attention load, whereas three out of four models with modified RAN subtasks under the condition of heavy attention load were statistically significant. These were: $R^2 = .533$, adjusted $R^2 = .416$, p = .024, for M-RAN-Symbolic-Large-Heavy (naming consonants), $R^2 = .561$, adjusted $R^2 = .451$, p = .017, for M-RAN-Non-Symbolic-Small-Heavy (naming pictures of animals), and $R^2 = .631$, adjusted $R^2 = .546$, p = .006, for M-RAN-Non-Symbolic-Large-Heavy (naming pictures of common objects).

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Table 4. Results of a multiple regression analysis of modified RAN (M-RAN-Symbolic-Small-Light) subtask performance by index of ballistic automaticity, CV-index of automaticity, and attention index

Variable:	r^a	R	R^2	R^2 change	*F* change	Sign. *F*	Final b
Ballistic automaticity	.262	.262	.069	.069	1.030	.327	.114
CV index of automaticity	.457	.466	.217	.149	2.469	.140	.388
Attention (Form B)	.409	.605	.366	.148	2.805	.120	.386

[a]Zero-order correlations. *p < .05, ** p < .01, *** p < .001

Table 5. Results of a multiple regression analysis of modified RAN (M-RAN-Symbolic-Large-Light) subtask performance by index of ballistic automaticity, CV-index of automaticity, and attention index

Variable:	r^a	R	R^2	R^2 change	*F* change	Sign. *F*	Final b
Ballistic automaticity	-.081	.081	.007	.007	.092	.766	-.166
CV index of automaticity	.211	.275	.076	.069	.975	.341	.235
Attention (Form B)	.670**	.708	.501**	.425**	10.221	.008	.654**

[a]Zero-order correlations. *p < .05, ** p < .01, *** p < .001

Table 6. Results of a multiple regression analysis of modified RAN (M-RAN-Non-Symbolic-Small-Light) subtask performance by index of ballistic automaticity, CV-index of automaticity, and attention index

Variable:	r^a	R	R^2	R^2 change	*F* change	Sign. *F*	Final b
Ballistic automaticity	-.058	.058	.003	.003	.047	.831	-.154
CV index of automaticity	.230	.281	.079	.075	1.065	.321	.259
Attention (Form B)	.521*	.575	.331	.252	4.515	.055	.503

[a]Zero-order correlations. *p < .05, ** p < .01, *** p < .001

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Table 7. Results of a multiple regression analysis of modified RAN (M-RAN-Non-Symbolic-Large-Light) subtask performance by index of ballistic automaticity, CV-index of automaticity, and attention index

Variable:	r^a	R	R^2	R^2 change	*F* change	Sign. *F*	Final b
Ballistic automaticity	-.077	.077	.006	.006	.083	.777	-.212
CV index of automaticity	.306	.373	.139	.133	2.007	.180	.359
Attention (Form B)	.502*	.604	.365	.226	4.279	.061	.477

[a]Zero-order correlations. *p < .05, ** p < .01, *** p < .001

Table 8. Results of a multiple regression analysis of modified RAN (M-RAN-Symbolic-Small-Heavy) subtask performance by index of ballistic automaticity, CV-index of automaticity, and attention index

Variable:	r^a	R	R^2	R^2 change	*F* change	Sign. *F*	Final b
Ballistic automaticity	-.193	.193	.037	.037	.543	.473	-.226
CV index of automaticity	.052	.238	.057	.019	.265	.615	.101
Attention (Form B)	.641**	.674	.454	.398*	8.751	.012	.632*

[a]Zero-order correlations. *p < .05, ** p < .01, *** p < .001

Table 9. Results of a multiple regression analysis of modified RAN (M-RAN-Symbolic-Large-Heavy) subtask performance by index of ballistic automaticity, CV-index of automaticity, and attention index

Variable:	r^a	R	R^2	R^2 change	*F* change	Sign. *F*	Final b
Ballistic automaticity	-.091	.091	.008	.008	.116	.738	-.154
CV index of automaticity	.164	.235	.055	.047	.647	.436	.181
Attention (Form B)	.706**	.730	.533**	.477**	12.259	.004	.693**

[a]Zero-order correlations. *p < .05, ** p < .01, *** p < .001

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Table 10. Results of a multiple regression analysis of modified RAN (M-RAN-Non-Symbolic-Small-Heavy) subtask performance by index of ballistic automaticity, CV-index of automaticity, and attention index

Variable:	r^a	R	R^2	R^2 change	F change	Sign. F	Final b
Ballistic automaticity	-.273	.273	.075	.075	1.130	.306	-.377
CV index of automaticity	.176	.410	.168	.094	1.465	.248	.283
Attention (Form B)	.650**	.749**	.561**	.392**	10.726	.007	.628**

[a]Zero-order correlations. *$p < .05$, ** $p < .01$, *** $p < .001$

Table 11. Results of a multiple regression analysis of modified RAN (M-RAN-Non-Symbolic-Large-Heavy) subtask performance by index of ballistic automaticity, CV-index of automaticity, and attention index

Variable:	r^a	R	R^2	R^2 change	F change	Sign. F	Final b
Ballistic automaticity	-.384	.384	.148	.148	2.425	.142	-.520*
CV index of automaticity	.199	.539	.291	.143	2.624	.129	.365
Attention (Form B)	.618*	.798**	.631**	.346**	11.425**	.005	.590**

[a]Zero-order correlations. *$p < .05$, ** $p < .01$, *** $p < .001$

Table 12. Results of a multiple regression analysis of modified RAN (M-RAN-High-Frequency-Bigram) subtask performance by index of ballistic automaticity, CV-index of automaticity, and attention index

Variable:	r^a	R	R^2	R^2 change	F change	Sign. F	Final b
Ballistic automaticity	.235	.235	.055	.055	.818	.381	.238
CV index of automaticity	.130	.239	.057	.002	.024	.878	.005
Attention (Form B)	.515*	.568	.322	.265	4.702	.051	.517

[a]Zero-order correlations. *$p < .05$, ** $p < .01$, *** $p < .001$

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Table 13. Results of a multiple regression analysis of modified RAN (M-RAN-Low-Frequency-Bigram) subtask performance by index of ballistic automaticity, CV-index of automaticity, and attention index

Variable:	r^a	R	R^2	R^2 change	F change	Sign. F	Final b
Ballistic automaticity	-.136	.136	.019	.019	.265	.615	-.203
CV index of automaticity	.142	.252	.064	.045	.625	.443	.187
Attention (Form B)	.573*	.613	.375	.312*	5.987	.031	.560*

[a]Zero-order correlations. *$p < .05$, ** $p < .01$, *** $p < .001$

All other models were non-significant, ranging in their overall explanatory power from 32.2 % (adjusted $R^2 = .153$, $p = .183$) in the M-RAN-High-Frequency-Bigram subtask to 45.4 % (adjusted $R^2 = .318$, $p = .056$, almost approaching the level of significance) in the M-RAN-Symbolic-Small-Heavy subtask (naming vowels under the condition of heavy attention load). In other words, this set of predictors was capable of explaining from 32 % to 63 % of variability in different modified RAN subtasks.

It is interesting to note that the most important predictor in practically all of the above analyses appeared to be the index of general attention. Its unique contribution varied across RAN subtasks, but was always higher than (or equal to, in one case) the contribution of either index of automaticity. Specifically, for the subtasks with the light attention load the attention factor alone explained: 14.8 % (adjusted R^2 change = .110, $p = .120$) of the variance in M-RAN-Symbolic-Small-Light subtasks (naming of vowels); 42.5 % of the variance (adjusted R^2 change = .442, $p = .008$) in naming consonants (M-RAN-Symbolic-Large-Light subtask); 25.2 % of the variance (adjusted R^2 change = .226, $p = .055$) in naming pictures of animals (M-RAN-Non-Symbolic-Small-Light subtask); and 22.6 % of the variance (adjusted R^2 change = .200, $p = .061$) in naming pictures of common unrelated objects (M-RAN-Non-Symbolic-Large-Light subtask).

In the case of the modified RAN subtasks associated with the heavy attention demand, attention alone explained even more variability in the criterion variables: 39.8 % (adjusted R^2 change = .407, $p = .012$) in naming vowels (M-RAN-Symbolic-Small-Heavy subtask); 47.7 % (adjusted R^2 change = .506, $p = .004$) in naming consonants (M-RAN-Symbolic-Large-Heavy subtask); 39.2 % (adjusted R^2 change = .410, $p = .007$) in naming pictures of animals (M-RAN-Non-Symbolic-Small-Heavy subtask); and 34.6 % (adjusted R^2 change = .364, $p = .005$) in naming pictures of unrelated common objects (M-RAN-Non-Symbolic-Large-Heavy subtask).

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Also, even in the presumably most automatized of all modified RAN subtasks – the one based on the High Frequency bigrams – the attention factor accounted for greater variance in naming performance than either of the indices of automaticity: R^2 change = .265, .241 after adjustment, p = .051 (compared to unadjusted 5.5% for ballistic automaticity and 0.2 % for the CV index of efficiency). Similar results were observed in the case of the Low Frequency bigram RAN subtask: R^2 change = .312, .299 after adjustment, p = .031 (unadjusted 1.9 % and 4.5 % for the ballistic and efficiency-related indices of automaticity, respectively).

Discussion

Before discussion the study findings with regard to its major research questions, it is important to mention that we, first, compared the obtained data structure with the results of [15]. There was no substantial difference, but one – with participants in the current study performing task of the Trail Making test Form B markedly faster. All other variables were compatible in their average values and variability between the two studies. This fact increases our confidence that the results obtained in the present study (despite its relatively limited sample) are reliable and likely to be representative of participants' performance on the RAN task and related measures.

Findings with Regard to Major Research Questions

The first two research questions concerned with how sensitive RAN task performance would be explicit manipulations of the attention demands and the source set size. As reported earlier, the ANOVA of performance time on the modified RAN subtasks yielded statistically significant main effects of stimuli type and attention load factors.

The observed pattern of results with regard to the first research question resembled most closely the projected scenario depicted in Figure 2. There were clear differences in naming time between symbolic and non-symbolic stimuli. However, in addition, difference was observed between subtasks involving the heavy versus light attention load, as illustrated in Figure 3. Finally, partly in accord with the pattern shown in Figure 5 attention load affected naming to different degrees in symbolic and non-symbolic RAN subtasks. These results once again demonstrate that participants take significantly longer to recognize and name aloud pictures than letters, as was repeatedly shown in the related literature (e.g., 3, 6, 8, 10, 16]. In agreement with the hypothesized outcomes and some of the previous research [e.g., 4, 6, 15], heavier attention demands slowed the naming process significantly across all stimuli types and set sizes, including symbolic ones. Given that light and heavy attention load conditions were perfectly matched in their mechanical components (pressing the space bar on a computer

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keyboard 5 times per individual subtask), the difference in naming time can be attributed solely to how much attention control was required for successful task execution. The heavy attention load condition presumably involved working memory (remembering the particular "target" combination of stimuli to respond to) to much greater extent than in the light attention load condition (press the space bar at the end of each line). This idea, in particular, is supported by research that implicated working memory in RAN task performance [e.g., 4, 20, 29, among many others]. It is of an additional interest that these attention-related results were combined with the low degree of involvement of automaticity measures in explaining variance in RAN task performance.

With respect to the second research question that addressed the effect of the source set size factor on the RAN task performance time, our study found no significant main effect of this manipulation. However, the results revealed a significant interaction effect involving source set size and stimulus type. We observed significantly faster naming of pictures of animals (drawn from the smaller source set, in agreement with what was expected) on non-symbolic RAN subtasks and of consonants (drawn from the larger source set, contrary to the original expectations) on symbolic RAN subtasks than on the corresponding smaller source set of symbolic stimuli (vowels) and larger source set of non-symbolic stimuli (objects).

Finally, in response to the third research question, the results revealed that naming of letters in the condition involving high frequency bigrams was faster than in the conditions involving low frequency bigrams. This result likely reflects the effect of reading practice (exposure to printed text) in symbolic RAN task performance.

The most important, in our view, of these results is the indication that performance on the RAN task largely reflects the attention demand, created by the specific task of naming stimuli, presumably making attention-related cognitive factors the major driving force of rapid naming, at least in the adult population. In addition, we observed that the source set size of the stimuli used in particular RAN subtasks can affect naming time, but here the results were more complex. When the stimuli were unlikely to be overlearned (pictures of animals and other objects), the fact that stimuli came from a large set size was associated with slower naming compared to stimuli from the smaller source set. This particular pattern of results implicates memory capacity into RAN task performance, at least with non-symbolic stimuli.

However, the same was not true for heavily practiced (routinely used) letters. The stimuli from the large source set (consonants) were named faster than stimuli from the smaller source set (vowels). This finding is paradoxical at first sight. If letter names are retrieved automatically, then there should be no real

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difference in naming consonant and vowels or just a marginal difference, but still in favour of stimuli from the smaller source set. Whatever the explanation for the reversed pattern is speculated – for example, that in a typical phonological training vowels tend to be more sustained in their pronunciation (i.e., produce longer lasting sounds), – one particular interpretation seems to be sufficiently plausible. It stipulates that the RAN task performance is unlikely to reflected automaticity of name retrieval alone.

To summarize this section of the discussion, the explicit manipulation of various factors influencing RAN task performance seems to point rather toward attention than toward automaticity account for naming speed. Stopping sort of definitively proclaiming just one major cognitive mechanism of RAN task performance, we would like, nevertheless, to once again suggest that 'A' in RAN could stand for 'attention' no less (if not considerably more) than for 'automaticity'.

Interrelations among Variables

In addition to the major research questions, this study also looked at relationships among variables, including RAN performance connection to reading rate. Perhaps, one of the most interesting results was that RAN subtask performance based on the low frequency bigrams correlated significantly with naming on all RAN subtasks except for the low attention demand task involving vowel naming and did so noticeably more strongly than with the subtask involving high frequent bigrams. One could probably speculate that this particular modification of the RAN task shares the most with either type of others – efficient recognition of highly practiced symbols and efficient management (presumably through higher attention control) of their more challenging (less familiar) combinations.

As it would be expected, all modified RAN subtasks under the condition of high attention load showed the strongest correlations with the primary measure of attention – Form B of the Trail Making test performance time. Also not surprisingly, all three significant coefficient of correlation between modified RAN subtasks and reading rate in participants' native language, involved symbolic stimuli. Moreover, and related to the last research question, both bigram-based modified RAN subtasks were highly correlated to L1 reading rate, providing yet another indication that practice with printed text is likely to strengthen RAN-to-reading association. Interestingly, performance on the subtasks utilizing less frequent, and hence less familiar, bigram patterns showed somewhat stronger correlations with reading than did more familiar highly frequent bigram subtasks. This particular pattern of results might reflect the possibility that more challenging tasks (the low frequency bigram condition) provided processing challenges that could differentiate strong performers better than did the easier tasks. If so, the same

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should be true for even more challenging (that is reading for comprehension) task. Consider also that, no matter how much processing of symbolic stimuli is automatized, more challenging tasks would still share some elevated attention demand.

Finally, the multiple regression analyses revealed that attention-related factors accounted for more variance in participants' performance on different RAN subtasks than did automaticity-related factors. The unique contribution of the index of general attention in some cases exceeded 40 % of explained variance in the case of several RAN subtasks, and not surprisingly, even more in subtasks with additional attention demands. Indeed, the association of attention with performance in the modified RAN subtasks appears to be higher than observed in the original RAN subtasks.

These results once again point to the importance of attention-related factors in RAN task performance. Consider that even four subtasks under the condition of light attention demand still in fact carried some extra load (presumably on working memory) of responding to the last stimulus in each row. As such, they were more dependent on attention-related factors, than the original RAN subtasks were. The contribution of attention to performance on four RAN modifications with the extra task of responding to particular combinations of targets was even higher. Very interestingly, in this subset of modified RAN subtasks, it appears that keeping track of more familiar (automatically recognized stimuli – vowel and consonant letters) in order to properly respond to their target combinations, took even more attention resources than it did for their more variable counterparts – presumably less automatically recognized pictures of animals and common objects.

Conclusion

To summarize, this study has shown that both symbolic and non-symbolic version of the RAN task are noticeably sensitive to direct manipulations of attention demand characteristics, resulting in significantly slower naming, when the attention demand is higher. More importantly, when attention was challenged, as it was in the high load condition, the connection of RAN task performance to reading (as well as the inter-correlations among different RAN subtasks) appeared to become stronger. Altogether, these findings suggest that it is the development of attention control that is likely to be strongly involved in successful rapid serial naming, although practice in reading by young adults is able to automatize the naming of symbolic stimuli. The latter observation is also in line with what previous meta-analyses [6, 7, 8] established about RAN-to-reading connections. The issue of balance between automaticity and attention-driven factors in naming is of interest not only to early literacy research and practice, but also to second language learning [e.g., 30].

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